International Journal of Power Electronics and Drive System (IJPEDS)
Vol. 8, No. 4, December 2017, pp. 1841~1851
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v8i4.pp1841-1851

Neural Adaptive Kalman Filter for Sensorless Vector Control of Induction Motor

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Article Info

Article history:

Received May 7, 2017
Revised Aug 30, 2017
Accepted Sep 14, 2017

Keyword:

ADALINE
Adaptive speed estimation
Artificial neural network
Field oriented vector control
Induction motor
Kalman filter
Sensorless control

ABSTRACT

This paper presents a novel neural adaptive Kalman filter for speed sensorless field oriented vector control of induction motor. The adaptive observer proposed here is based on MRAS (model reference adaptive system) technique, where the linear Kalman filter calculate the stationary components of stator current and the rotor flux and the rotor speed is calculated with an adaptive mechanism. Moreover, to improve the performance of the PI classical controller under different conditions, a novel adaptation scheme based on ADALINE (ADAptive LInear NEuron) neural network is used. It offers a solution to the PI parameters to stabilize automatically about their optimum values and speed estimation to converge quicker to the real. The proposed adaptive Kalman filter represents a good comprise between estimation accuracy and computationally intensive. The simulation results showed the robustness, efficiency, and superiority of the proposed scheme compared to the classical method even in low speed region.

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1. INTRODUCTION

The Field oriented control of induction motor (IM) requires the knowledge of rotor speed and stator current measurement [1]. However, the speed sensor cannot be mounted in some case due to exit difficulties in maintaining this speed sensor, make the system easy be disturbed and their high cost.

Sensorless speed control of induction motor can avoid fragility of the mechanical sensor, eliminate the difficulty of mounting the sensor and reduce cost in many applications [1]. There are plenty of literature works concerning speed sensor algorithms among them, the state observers. His principle based on the IM dynamic equations [2]. In general, observers can be classified into two domains, stochastic and deterministic.[3] The optimal estimate of stochastic observers is based on noise elimination (for example Kalman filter KF). As long as the deterministic neglect them (Luenberger, MRAS (model reference adaptive system). The MRAS method is based on the comparison between the outputs of two estimates [4]. The output errors are then used to drive a suitable adaptation mechanism that generates the estimated speed [5-8]. The MRAS rotor flux is the most popular MRAS strategy, the main problem of model-based sensor drive are related low-speed range.

While the induction motor model is a stochastic system, the optimal rotor speed estimation is well illustrated by Kalman Algorithm. The speed is considered as a state. The extended version of Kalman filter (EKF) designed for non-linear system shows a good performance even in low speed [9], [10]. Not only, to

estimate rotor flux and speed but also EKF is used to correct and diagnose by estimating parameters (Rr, Rs, …) [9]. Besides, other works extended IM model in order to estimate torque load for compensating and eliminate the static error. Whenever the system is more extended, the all estimation is more precise and the computationally cost becomes more intensive. This filter my not be appropriate in situation. So, instead of using 5 order model or more, 4 order linear KF is enough to estimate rotor flux. And the rotor speed is calculated with the adaption mechanism [11]. Mora and al [11], compared between adaptive speed estimation based on linear KF, straightforward EKF [12], and speed adaptive flux observer [6]. The results show in a real application that the sample time of EKF is greater 5 times than the adaptive one and a good performance in low speed compared with adaptive flux observer. So the linear KF is suitable for use with complex structures that demand high computational requirements. Based on his advantages linear Kalman filter is selected in this work to estimate rotor flux.However, rotor speed is calculated with adaption mechanism. PI regulators are the most useful adaptation schemes for adaptive observers to generate the estimated rotor speed. However, PI gains are fixed for the entire operating time of the observer. They characterize the response of the estimator. They are chosen with "try and error" tests. i.e., still groping until the results are satisfying. In other ways, the system attitude changes with time that makes these gains invalid for all operating conditions. For this, many solutions are proposed such as advanced adaptation mechanisms, fuzzy logic controller [13], [14] sliding mode adaption [15], [16], and ANN algorithms (BPN learning low [17]).

In this study, we explore the possibility to ameliorate adaptive Kalman filter with new adaptation scheme. It consists to separate the estimation of rotor flux and rotor speed in two sequential stages. Where the stator currents and the rotor flux are calculated by linear Kalman filter and speed is consider as the output of PI corrector. And the method that we propose to ameliorate the speed adaptation mechanism guarantees precision and optimization of the estimation. It is an "intelligent" technique based on the algorithms of ANN. We propose to determine PI parameters by using ADALINE (ADAptive LInear NEuron), this method is motivated by the need of the simplicity and flexibility in ANN (it should adapt only one weight); the main advantage of this technique according to its Simplicity algorithmic comparing with other similar methods [18].

2. VECTOR CONTROL OF INDUCTION MOTOR

2.1. Modeling of Induction Motor

Using simplifying assumptions, the state equations of an induction motor in rotor speed reference frame can be expressed as follows:

$$\begin{cases} \dfrac{d}{dt}x = A(x) + B(u) \\ y = Cx \end{cases} \tag{1}$$

Where:

$$x = \begin{bmatrix} i_{sd} & i_{sq} & \varphi_{rd} & \varphi_{rq} \end{bmatrix}^T,\ u = \begin{bmatrix} v_{sd} & v_{sq} \end{bmatrix},\ y = \begin{bmatrix} i_{sd} & i_{sq} \end{bmatrix}^T$$

$x(t)$ The state vector
$u(t)$ The control input
$y(t)$ The output.
v_{sd}, v_{sq} Stator voltages in fixed reference frame [V].
i_{sd}, i_{sq} Stator currents in fixed reference frame [A].
$\varphi_{rd}, \varphi_{rq}$ Rotor flux in fixed reference frame [Wb].
$L_r, L_s/M_{sr}$ Rotor, stator /mutual inductances [H]
R_r, R_s Rotor, stator resistances [Ω].

$$A=\begin{bmatrix} -\left(\dfrac{R_s}{\sigma L_s}+\dfrac{1-\sigma}{\sigma\tau_r}\right) & \omega_r & \dfrac{L_m}{\sigma L_s L_r}\dfrac{1}{\tau_r} & \omega_r\dfrac{L_m}{\sigma L_s L_r} \\ -\omega_r & -\left(\dfrac{R_s}{\sigma L_s}+\dfrac{1-\sigma}{\sigma\tau_r}\right) & -\omega_r\dfrac{L_m}{\sigma L_s L_r} & \dfrac{L_m}{\sigma L_s L_r}\dfrac{1}{\tau_r} \\ \dfrac{L_m}{\tau_r} & 0 & -\dfrac{1}{\tau_r} & 0 \\ 0 & \dfrac{L_m}{\tau_r} & 0 & -\dfrac{1}{\tau_r} \end{bmatrix} B=\begin{bmatrix} \dfrac{1}{\sigma L_s} & 0 \\ 0 & \dfrac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, C=\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

2.2. Principal of Direct Field-Oriented Vector Control

The Principe of vector control of induction motor consists to regulates the flux by a current component ids and the torque by the other component iqs. So, it's necessary to apply a decoupling technique between torque and flux. To comply with this condition:

$$\begin{cases} \varphi_{rd}=\varphi_r \\ \varphi_{rq}=0 \end{cases} \qquad (2)$$

With field orientation, the dynamic equations of stator current components, rotor flux, and electromagnetic torque are given by:

$$\begin{cases} \dfrac{di_{sd}}{dt}=\dfrac{1}{\sigma L_s}\left(-\left(R_s+(\dfrac{M_{sr}}{L_r})^2 R_r\right)i_{sd}+\sigma L_s\omega_s i_{sq}+\dfrac{M_{sr}R_r}{L_r^2}\phi_r+V_{sd}\right) \\ \dfrac{di_{sq}}{dt}=\dfrac{1}{\sigma L_s}\left(-\left(R_s+(\dfrac{M_{sr}}{L_r})^2 R_r\right)i_{sq}-\sigma L_s\omega_s i_{sd}+\dfrac{M_{sr}R_r}{L_r^2}\phi_r\omega_r+V_{sq}\right) \\ \dfrac{d\phi_{rd}}{dt}=\dfrac{pM_{sr}}{L_r}i_{sd}-\dfrac{R_r}{L_r}\phi_r \\ T_e=\dfrac{pM_{sr}}{L_r}i_{sq}\phi_r \end{cases} \qquad (3)$$

Figure 1 shows direct field-oriented control (DFOC) structure. The stator currents are regulated by PI controllers, while speed by an IP. The reference voltages V_{sq}^* and V_{sq}^* require the flux and torque desired via PWM drive system.

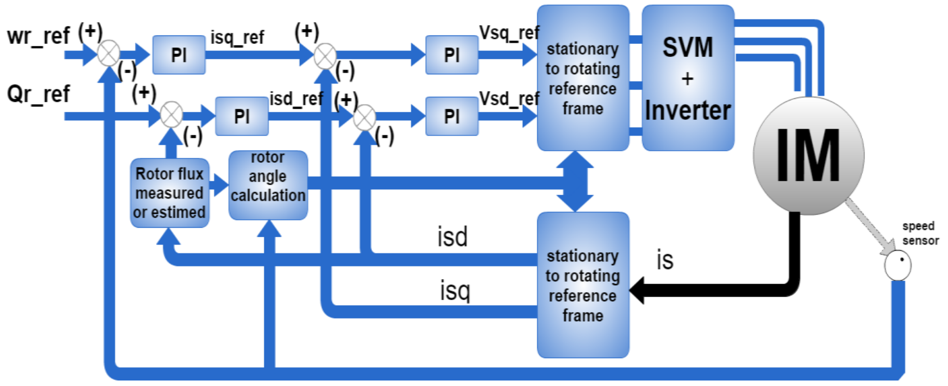


Figure 1. Induction Motor Vector Control Structure

3. NEURAL KALMAN FILTER NKF

Principal of this adaptive observer considers putting linear Kalman filter and neural adaptive scheme of speed estimation in cascade. That means, rotor flux and stator currents estimated by KF are used as inputs in calculate rotor speed and the latter is used as a parameter (not as a state like in EKF) in KF model.

3.1. Kalman Filter Algorithm

In many stochastics processes, it is necessary to take into account the noises in order to realize the optimum estimation. The Kalman filter algorithm is the most utilised to illustrate that estimation that's why we use the term "filter". Define the discrete the system model as follows:

$$\begin{cases} \dot{x}(k+1) = A(k)x(k) + B(k)u(k) + w(k) \\ y(k) = C(k)x(k) + v(k) \end{cases} \tag{4}$$

Where
$w(k)$: random noise matrix of state model.
$v(k)$: random noise matrix of output model.

Based on the above dynamic model, we apply the following Kalman filter algorithm:

a. Prediction of state:

$$\hat{x}(k+1/k) = A(k)\hat{x}(k/k) + Bu(k) \tag{5}$$

b. Estimation of error covariance matrix:

$$P(k+1/k) = A(k)P(k/k)A^T + Q(k) \tag{6}$$

c. computation of Kalman filter gain:

$$K(k+1) = P(k+1/k)C^T(k+1) \times [C(k+1)P(k+1/k)C^T(k+1) + R(k+1)]^{-1} \tag{7}$$

d. Update of the error covariance matrix:

$$P(k+1/k+1) = [I - K(k+1)C(k+1)]P(k+1/k) \tag{8}$$

e. state estimation:

$$\hat{x}(k+1/k+1) = \hat{x}(k+1/k) + K(k+1)\left\{y(k) - C\left[\hat{x}(k+1/k)\right]\right\} \tag{9}$$

3.2. Discrete State Model of IM

It is important to have a dynamic representation based on the stationary reference frame. So as to acquire a better estimate. And to apply Kalman filter algorithm, it is also necessary to discretize induction motor model by using a first-order expansion. The state variables dynamic model in the stationary reference frame consisting only linear equations can be written as:

$$\begin{cases} \dot{x}(k+1) = A_d x(k) + B_d u(k) \\ y(k) = Cx(k) \end{cases} \tag{10}$$

Where:

$$\begin{aligned} A_d &= e^{ATe} \approx I + ATe \\ B_d &= A^{-1}(e^{ATe} - I)B \approx BTe \end{aligned} \tag{11}$$

$$A_d=\begin{bmatrix} 1-\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right)Te & \omega_r Te & \frac{L_m}{\sigma L_s L_r}\frac{1}{\tau_r}Te & \omega_r\frac{L_m}{\sigma L_s L_r}Te \\ -\omega_r Te & 1-\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right)Te & -\omega_r\frac{L_m}{\sigma L_s L_r}Te & \frac{L_m}{\sigma L_s L_r}\frac{1}{\tau_r}Te \\ \frac{L_m}{\tau_r}Te & 0 & 1-\frac{1}{\tau_r}Te & 0 \\ 0 & \frac{L_m}{\tau_r}Te & 0 & 1-\frac{1}{\tau_r}Te \end{bmatrix},\ B_d=\begin{bmatrix} \frac{1}{\sigma L_s}Te & 0 \\ 0 & \frac{1}{\sigma L_s}Te \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

3.3. Speed Estimation

The advantage of NKF consists of minimizing cumbersome of calculating. It is because the used of the system model of the induction motor is fourth-order and not more. And Speed feedback is implemented in flux observer.

The estimation error of stator currents and rotor flux is given by:

$$e = x-\hat{x}\left[k+1/k+1\right] \tag{12}$$

Derivate of the error:

$$\frac{d}{dt}e=(A+KC)e-\Delta A\hat{x} \tag{13}$$

$$\Delta\omega_r=\hat{\omega}_r-\omega_r\ ,\ c=\sigma L_s L_r / L_m Te\ ,\ J=\begin{bmatrix}0 & -1\\ 1 & 0\end{bmatrix}$$

We use the same Lyapunov function that Kubota used in [6]:

$$V=e^T e+(\hat{\omega}_r-\omega_r)^2/\lambda \tag{14}$$

λ: a positive constant.

$$\frac{d}{dt}V=e^T\left\{(A+KC)^T+(A+KC)\right\}e-2\Delta\omega_r\left(\varepsilon_d x\left[k+1/k\right]_4-\varepsilon_q x\left[k+1/k\right]_3\right)/c+2\Delta\omega_r\frac{d}{dt}\hat{\omega}_r/\lambda \tag{15}$$

Where:

$\varepsilon_d=i_{sd}-x\left[k+1/k\right]_1$ and $\varepsilon_q=i_{sq}-x\left[k+1/k\right]_2$

Here, $x\left[k+1/k\right]_n$ represents the estimed states that are calculated with KF.

$$\frac{d}{dt}\hat{\omega}_r=\lambda\left(\varepsilon_d x\left[k+1/k\right]_4-\varepsilon_q x\left[k+1/k\right]_3\right)/c \tag{16}$$

The speed can be written in the following integral adaptive scheme [6]:

$$\hat{\omega}_r=K_p(\varepsilon_d x\left[k+1/k\right]_4-\varepsilon_q x\left[k+1/k\right]_3)+K_i\int(\varepsilon_d x\left[k+1/k\right]_4-\varepsilon_q x\left[k+1/k\right]_3)dt \tag{17}$$

This expression is usually used in speed adaptive flux observers for induction motor using the difference between currents (measured and estimated) and observed flux, ADALINE adjusts proportional K_p and integral K_i adaption gains.

3.4. ADALINE for Adaptive Scheme Speed Estimation

In our work, the idea consists to replace PI parameter by an ANN structure, to increase the robustness of the adaptive scheme. Which makes the observer reliable under various conditions. For a high

learning, ADALINE is selected among other ANN structures. This choice is because it is fast and simplest to imply.

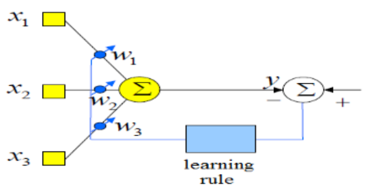


Figure 2. ADALINE Learning Rule

$$y_k = \sum_{i=1}^{n} x(i)_k w_k = x_i^T w_k \tag{18}$$

Graphically, an ADALINE is represented by the topology shown in Figure 2 where *y(k)* is the ADALINE output, *w(k)* is the weight vector of dimension (1×n), and *x(k)* is the ADALINE input vector of dimension *(n×1)* [18].

$$w_{k+1} = w_k + \Delta w \tag{19}$$

A block diagram of the proposed neural adaptive scheme is illustrated in Figure 3.

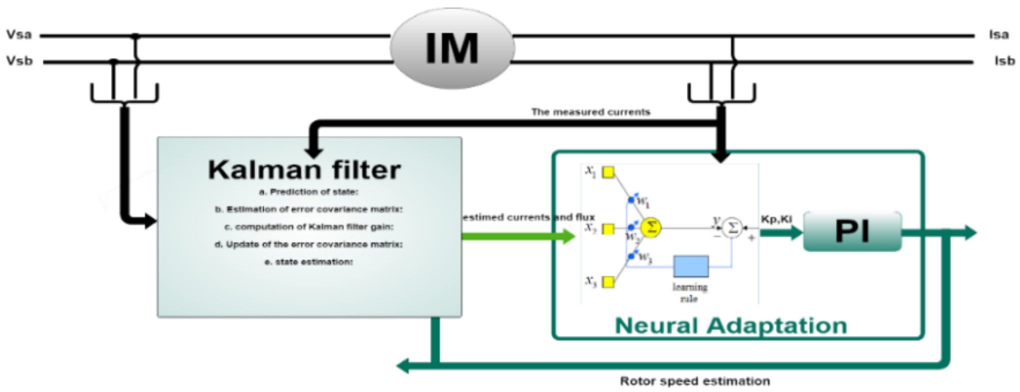


Figure 3. Block Diagram of Neural Speed Observer

The main difference between neural Kalman and the classical one is that ADALINE operates on PI parameters in each new iteration with the respect to give sophisticated values. More precisely, the learning rule updates this gains according to variation in operating condition to values necessary for obtaining accurate estimation.

4. SIMULATION RESULTS

To evaluate the performance of Neural adaptive Kalman filter in sensorless control of three-phase induction motor a comparison between the proposed method and the classical adaptive Kalman filter is made. Classical Kalman has been adapted with Kubota’s method. It was difficult to find the gains KP and Ki to have a good estimation of speed with "try and error" method. NKF is easier to synthesize because we do not have to grope the gains (it is done automatically). It is enough to apply the algorithm of ADALINE and the sophisticated PI parameters have been got.

The observers are simulated using MATLAB/Simulink software. The block diagram of the control system is illustrated in Figure 4 the motor parameters are given in Table 1. Vector control use a PMW

switching and power converter. It is well noted that in the comparison, the same machine, the same the vector control, the same Kalman filter algorithm with the same covariance matrices and the same sampling period are used. The only difference is in the adaptive mechanism. The estimated rotor speed and flux are used for closed control loops.

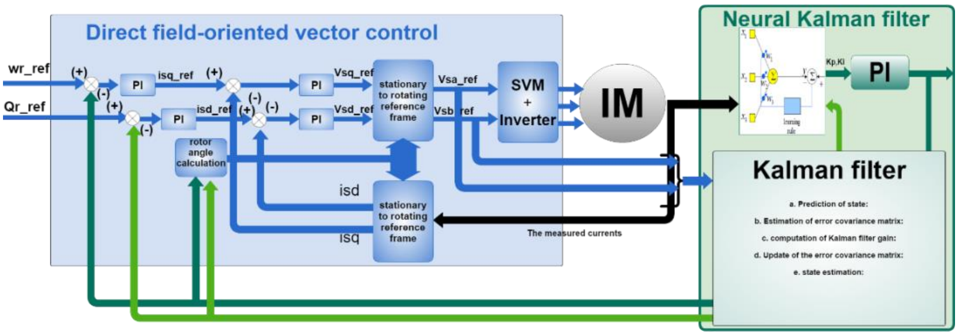


Figure 4. Block Diagram of the Sensorless Control of Induction Motor

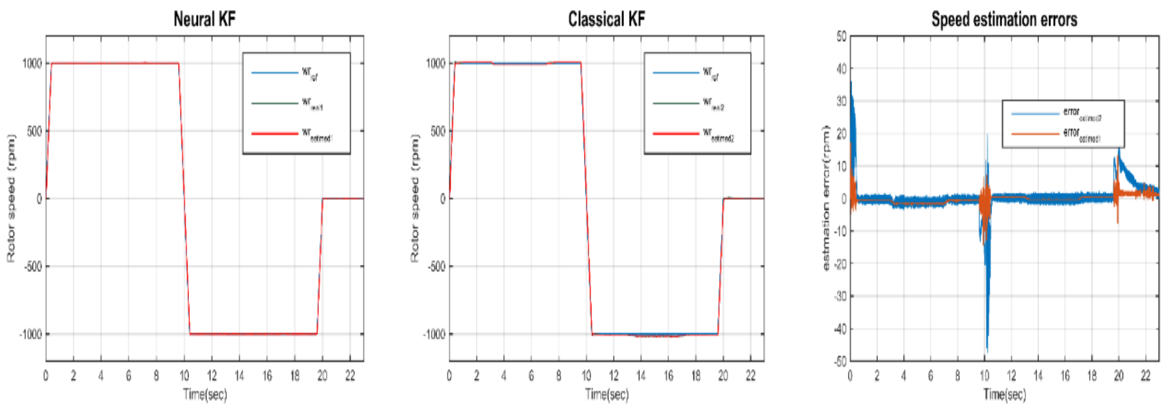
Table 1. Parameters of the IM

parameters	values	units
R_s	1.2	Ω
R_r	1.8	Ω
L_s	0.1554	H
L_r	0.1566	H
M_{sr} L_m	0.15	H
P	2	-
Rated speed	1440	Rpm
Rated power	5.36	HP

4.1. Speed Reversal

Figures 5 to Figure 12 show the Rotor response to a step speed command of ±1000 rpm with application of step load torque 15N.m during seconds in each trapezoidal. Note that wr_{estim1} is the speed estimated by Neural KF and wr_{estim2} by the classical. Speed responses wr_{real1} and wr_{real2} of the system with feedback from the filters follow perfectly the reference.

It is remarkable that peak values of speed in transient states of the proposed adaptation are less than the classical method (Figure 8) and its static estimation error is null. It adapts faster because of the best gains calculated and corrected with ADALINE that allows neural KF to ensure the better estimation even in rapid speed reversal.



(a) (b) (c)

Figure 5. Rotor Speed Estimation using (a) NKF (b) Classical KF (c) Speed Estimation Errors

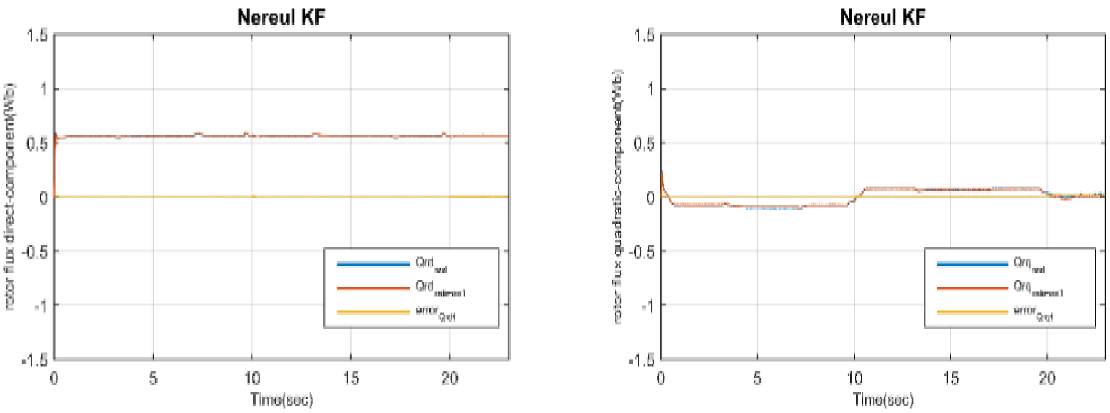


Figure 6. Rotor Flux Components Estimated by Neural KF

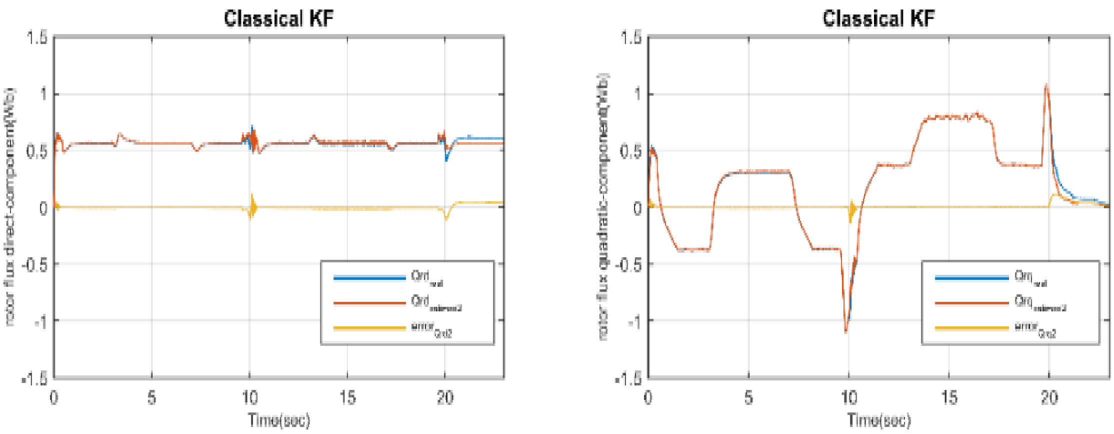


Figure 7. Rotor Flux Components Estimated by classical KF

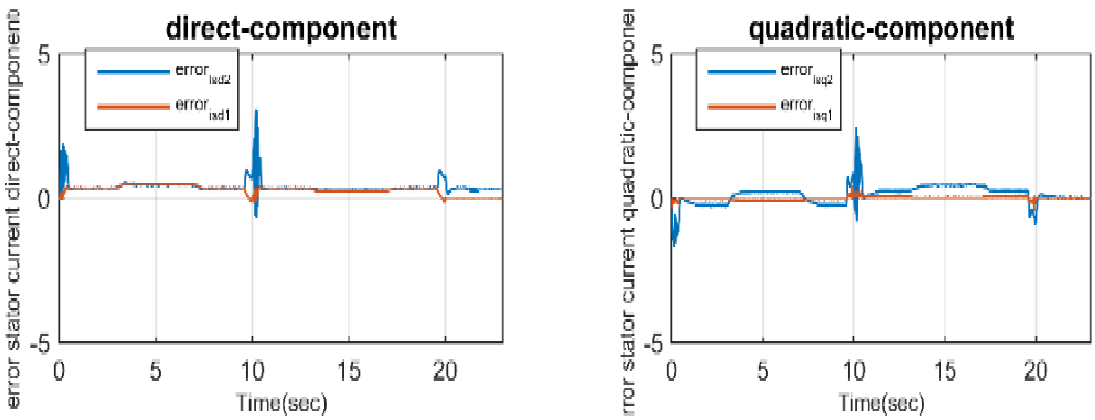
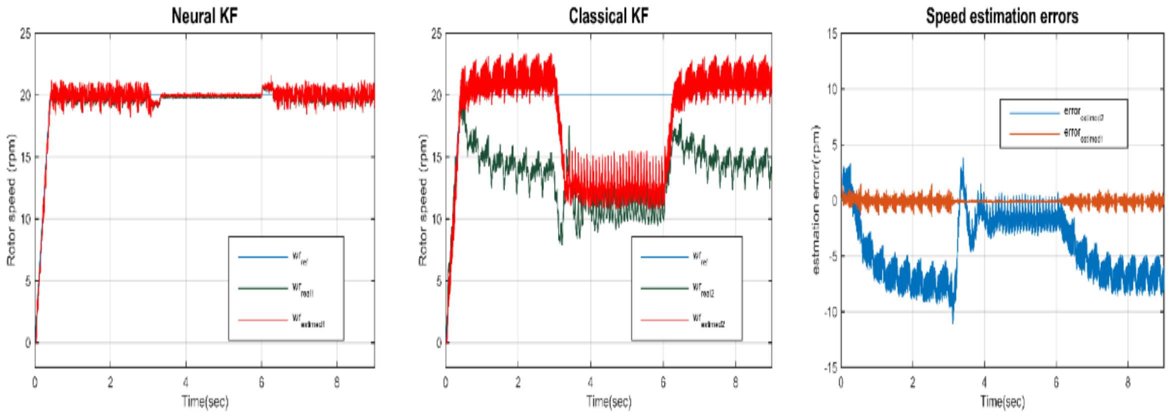


Figure 8. Stator Currents Components Estimation Errors

Figure 9 and Figure 10 present rotor flux responses of both observers. When reference speed is reversed, the rotor flux estimation errors using classical KF increase. While NKF eliminates this errors. It because a good rotor speed observation guarantees a good rotor flux estimation by what the speed is used as a feedback in the estimation of flux. Furthermore, NKF adaption mechanism uses sophistic gains for calculate rotor speed consequently, its rotor flux and stator currents estimated (Figure 11 and Figure 12) are more

accurate. A comparison of speed responses of both observers at high reference shows that is neural Kalman works well it is because ADALINE guarantees the adjustment of gains even in the transient state.



(a) (b) (c)

Figure 9. Rotor Speed Estimation using (a) NKF (b) Classical KF (c) Speed Estimation Errors

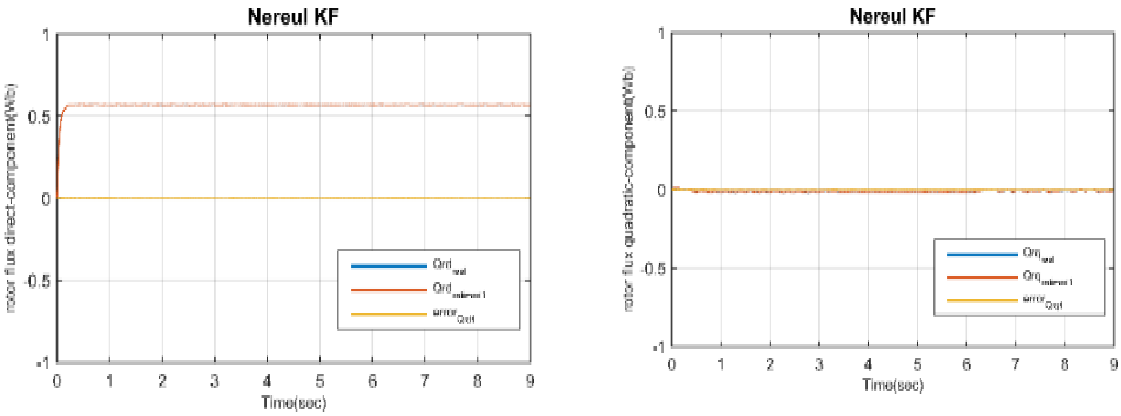


Figure 10. Rotor Flux Components Estimated by Neural KF

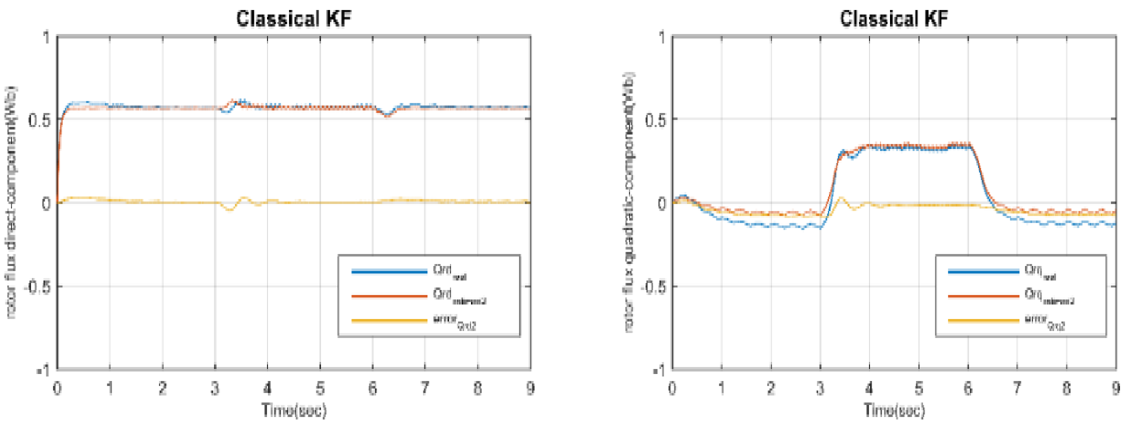


Figure 11. Rotor Flux Components Estimated by Classical KF

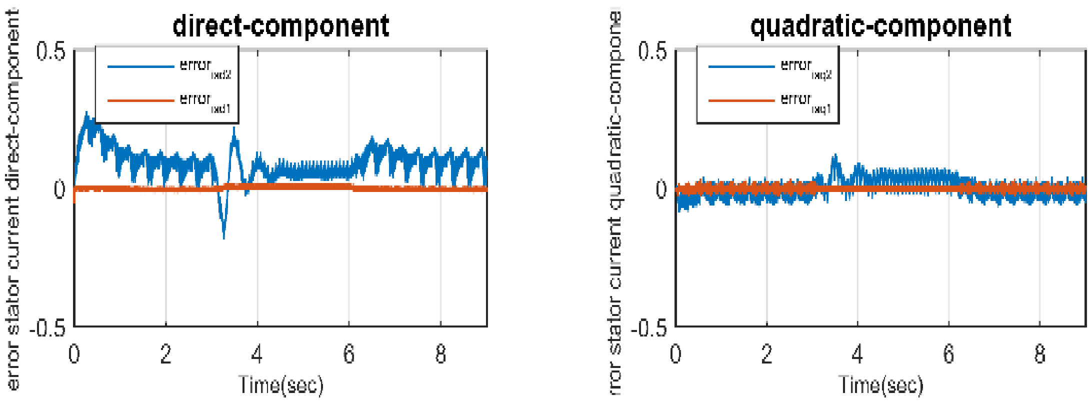
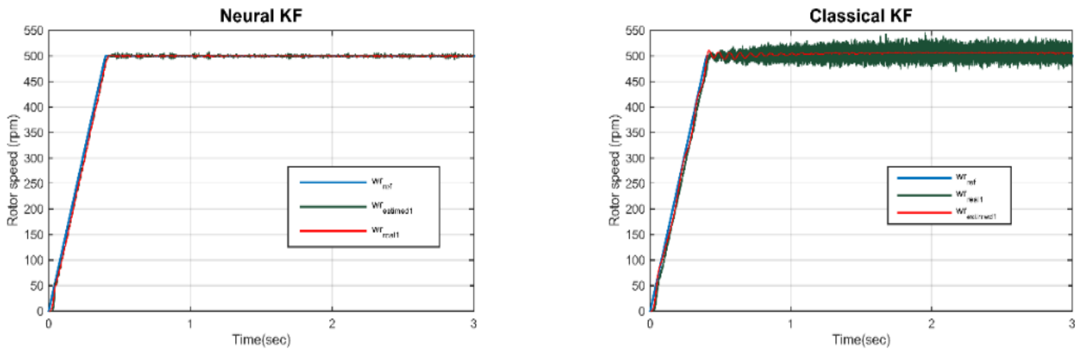


Figure 12. Stator Currents Components Estimation Errors

4.2. Low Speed Range

In Figure 13 and Figure 14, the simulation results of the rotor speed control performed by the estimated speeds and flux under low reference speeds 20 rpm with 10N.m step load torque applied in interval [3 6]s. In this difficult operating conditions, neural filter works better than the classical.



(a) (b)

Figure 13. Rotor Speed Estimation using (a) NKF (b) Classical KF

In Figure 16 and Figure 17, it can be observed that sensorless DFOC drive of IM using NKF works well, it garantee a good decoupling between torque and flux (φ_{rq}=0). With stator currents errors tend to zero even in low speed and under a load torque. From these results, the sensorless control scheme using neural KF has a good estimation accuracy because of ADALINE intelligence.

4.3. Noise Injection

To verify the effect of the measurement noise we inject the same white noise signal in currents component -alpha & beta- in both observers

Figure 19 presents the speed response using NKF and Figure 20 presents the response using classical adaptive KF.

The effectiveness of the learning algorithm is so clear. It minimizes estimation error in comparison with the classical. The Adaline makes Kalman filter works better.

Finaly, one can see that classical KF is less efficient than the Neural KF in all diffirents cases (speed reversal, load torque aplication , noise injected and in low speed range) it because PI parameters learned with ADALINE is more performed.

5. CONCLUSION

New observer structure was presented in our work that estimates rotor speed and rotor flux for sensorless direct rotor field-oriented vector control of induction machine. Its principal combines linear Kalman filter with the neural adaptive mechanism. The combination gives observer both performances: intelligent adaption (accuracy and robustness) and reduces the complexity (less computational requirement). The learning rule of ADALINE allows the calculations of sophisticated PI parameters for the perfect adaption of the rotor speed. Consequently, estimated stator currents and rotor flux are more accurate. A comparison with classical adaptive Kalman shows the good performances of our method.

The efficiency of ANN in control of electrical systems has been proved once again. Our future investigations concern an implementation of this method in other observers.

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